China's regional assessment of renewable energy vulnerability to climate change

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ABSTRACT

Renewable energy development is a major response to address the issues of climate change and energy security. The utilization of renewable resources, however, highly depends on the climate conditions, which may be impacted in the future due to global climate change. Based on literature analysis, this paper presents a general framework for renewable energy vulnerability assessment and applies grey cluster analysis method to demonstrate the features of vulnerability, and then employs the Simple Additive Weighting Approach to address the multiple-attribute decision problems of vulnerability assessment in China. The categorized results imply that the proposed index system is suitable for decision-making analysis and comparative analysis of renewable energy vulnerability to climate change in China. In terms of exposure part, the cluster results are complex and varied due to the unique combination of natural factors, social factors and the energy structure. In the sensitivity section, the results are presented on the distribution of areas rich in hydropower, wind power and solar energy potential. Moreover, the main results of this study are the higher renewable energy vulnerability of the poorer regions of China to climate change and the relative higher importance of adaptive capacity building in vulnerability management. Finally, policy recommendations on regional renewable energy vulnerability management are also made.

Contents

1. Introduction

1.1. Renewable energy development in China

The urbanization and economic growth in China has stimulated an unprecedented surge for energy demand [1]. Electricity blackouts or even electricity shortages happened frequently in many provinces when cold weather impacts the power system by driving up demand for heating [2,3]. Meanwhile, China will face serious challenges in terms of energy security, climate change and environmental protection in the future unless sustainable economic development can be achieved without ramping up its dependence on oil and coal imports. Consequently, as highlighted by the International Energy Agency [4] and [5,6], the development of renewable energy (RE) has been widely acknowledged by the international community as an important means to address these issues. Chinese government's persistent policies for energy security with a top priority attached to the RE development included the ambitious goal that the energy from renewable sources should constitute 15 percent of the primary energy by the year 2020 [7].

With these clear targets, RE in China has witnessed rapid growth between 2006 and 2010 and the overall strength as well as competitiveness of this industry has made remarkable progress, resulting from the improvement of Chinese energy system. By the year 2010, the installed capacity of hydropower in China has reached 216.1 GW, nearly double of what was in 2005, while the hydro-electricity power generation amounted to 686.7 billion kWh, making up 16.2% of the total electricity generation in China [8]. As for the wind power, after four years of rapid growth with an annual growth rate of over 100% since 2005, the installed capacity of grid-tied wind power ranked first in the world in 2010, totaling 31 million kW in 2011 [8]. Moreover, the aggregate installed area of solar water heating system has reached 0.168 billion square meters, replacing 20 Mtce in the use of fossil fuel. The recent 12th five year plan (2011–2015) on RE development released by Chinese government cleared the blueprint of renewable energy, implying a more important role that the rapid development of RE will be playing in the near future in terms of the stability of energy supply, the energy structure adjustment as well as the sustainable economic development [9].

1.2. Relationship between renewable energy and climate change

The energy utilization in the world, especially the use of renewable energy, has been increasingly affected by climate change [10]. It points out the dual relationship between RE and climate change: development of the former is one of the most significant measures to deal with the latter whilst the latter has profound impacts on the former. For example, according to IPCC [11], the extreme events had tremendous influences on renewable energy system. Other factors, such as the renewable technology, the imperfection of management system for RE and small investment in RE industry, have become the bottlenecks for RE development in the world, especially in China [12].

The issues of energy security and climate change have drawn increasing attention from the international community to research on RE vulnerability, which plays an indispensable role in identifying the climate risks of RE development. As for the research in developed countries, the U.S. Climate Change Science Program issued in 2007 [13] estimated the impacts of climate change on the production and utilization of electric power in America and concluded that renewable energy would play a key role in climate change mitigation and low carbon emissions, but its high dependence on the climate conditions would render it vulnerable to climate change. The report "Climate Impacts on Energy Systems" released by the World Bank demonstrated the direct effects of climate change on energy systems including energy supply and demand, energy endowments, energy infrastructure and energy transportation as well as the indirect effects of climate change on energy systems through other economic sectors [14]. Based upon the review of climate impacts on electricity markets, Torben and Steffen [15] analyzed the influences of climate change on the electric power market in terms of electricity supply and power demand, and identified some significant gaps in the present research, such as regional studies of demand side impacts for Africa, Asia, the Caribbean and Latin American. Breslow and Sailor analyzed potential impacts of climate change on wind speeds in the continental United States and found that even though there is still a great deal of uncertainty about future changes of wind fields, climate variability and long term climate change in citing wind power facilities should be considered [16]. With more credible scenarios, the follow-up study [17] focused on regional analysis of wind power vulnerability to climate change and the reduction in generation potential of wind power was deduced in this study. Pryor and Barthelmie presented the mechanisms of Climate change impacts on wind energy and illustrated the relevant studies in northern Europe [18].

The RE vulnerability of developing countries also attracted considerable attention. Pereira et al. applied the forecasts from a climate model to evaluate the impacts of climate change on wind power density in Brazil and concluded that those scenarios are suitable for wind power exploitation in Brazil in the long run [19]. As for hydropower generation, Wang et al. applied grey forecasting model to quantify the vulnerability of hydropower generation to climate change in China and found the increasing hydropower vulnerability of the poorest regions and the main hydropower generation provinces of China to climate change [20]. Based on the seasonal ARMA model, Lucena et al. analyzed the vulnerabilities of renewable energy production in Brazil for the cases of hydropower generation and liquid biofuels production, and pointed out the increasing energy vulnerability of the poorest regions of Brazil to global climate change [21]. Subsequently, Lucena et al. analyzed the possible impacts of climate change on the wind power potential by employing the 'delta method', and concluded that wind power potential in Brazil would not be jeopardized by future climate conditions [22]. Rivza et al. studied the risks facing sustainable development of bioenergy production in Latvia by using Analytic Network Process and

listed several policy implications in different stages of risk management [23].

1.3. The aim of this paper

After reviewing the literatures on vulnerability assessment, this paper demonstrates a universally applicable framework for RE vulnerability assessment, and then applies the Grey Cluster Analysis (GCA) to test and verify the feasibility of this framework, in a bid to further explore features of the regional RE vulnerability in China. Hence, we employ the Simple Additive Weighting Approach to tackle the multiple-attribute decision-making problems of RE vulnerability assessment at regional level in China. Based upon those comparisons and the results, this paper proposes some implications, which would shed light on the identification of climate change risk and the increasingly aggravated energy security issues.

This RE vulnerability assessment framework provides a means of making comparisons between different regions to tackle questions such as:

1. Which regions are most vulnerable to global change with reference to renewable energy system?
2. How do the vulnerabilities of two regions compare?
3. Which dimension of vulnerability dominate the RE vulnerability assessment?
4. What are the features of RE vulnerability in China?

The remainder of this paper is organized as follows. In Section 2, the indicators for renewable energy vulnerability assessment are selected based on the literature analysis. Then, the model and approach used for the identification of vulnerable features, the decision-making analysis as well as the data resources are introduced in Section 3. Section 4 involves the results and discussion. Finally, Section 5 concludes the paper and makes some recommendations.

2. Definition of RE vulnerability based on literature review

There are numerous studies on the definition of vulnerability [24–26]. Based on the connotation of vulnerability in IPCC 2001, Metzger et al. [27] merged the exposure unit and sensitivity unit into a new unit namely 'Potential impacts' and drew the vulnerability map for an ecosystem. Through combing the development thread of the vulnerability concept, Füssel [28] constructed the general conceptual framework for climate change vulnerability research and emphasized the limited adaptive capacity of a system. Based on the description in IPCC 2007 [29], vulnerability is the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the nature, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity. Furthermore, Polsky et al. [30] assumed that vulnerability is a function of three main dimensions: exposure to specific social and/or environmental stresses, associated sensitivities, and related adaptive capacities and emphasized the limited adaptive capacity inherent in the system. This work facilitated the construction of comparable global change vulnerability assessments for a vulnerability scoping diagram (VSD) and its application to a case study known as the HERO project. Until now, the VSD has a widespread application in the fields of community management [31], water systems [32], coastal tourism [33] and brownfield redevelopment [34].

According to these concepts of vulnerability, we define the renewable energy vulnerability in three dimensions: exposure of RE to climate change, sensitivity of RE to climate change and adaptive capacity of RE system, the exact meanings of which will be detailed as follows.

2.1. Exposure of RE to climate change

We define exposure as the degree to which a region's RE system is subject to climate change due to anthropogenic threats. Exposure is estimated using scores of cumulative impacts that quantify the threat to the region's RE system from a set of 4 components.

In particular, the exposure of renewable energy can be divided into five components, namely historical overview on extreme weather events, the situation of land use, economic exposure, population exposure and the exposure of energy structure. Extreme events [35] refer to the frequency of storm winds, extreme rainstorms, floods and frozen, which reflect the possibilities of extreme events in the near future. The item, land use, represents the changes of landform, which has impacts on wind power and hydropower generation and is represented by the forest coverage. Energy structure exposure is the proportion of RE in each region. Moreover, Economic and population exposure [30,36] are measured respectively by the regional GDP per unit area and population intensity multiplied by the proportion of RE consumption in each province, implying that the energy structure exposure is embodied in the economic and population exposure. Thus, the exposure unit is condensed into four components: land use, extreme events, exposure population and economic exposure.

2.2. Sensitivity of RE to climate change

Sensitivity can be defined as the degree to which a region depends on RE. For each region, the dependence on RE and climatic factors (including rainfall, wind, sunshine, temperature, and humidity), which are closely related to the development of RE, are chosen to measure the sensitivity of RE to climate change.

Climate elements are selected as the universally acceptable indicators of sensitivity because of the inseparable relationship between RE utilization and these climatic factors. Hydropower, wind power, solar power and other kinds of RE generation are closely related to the stable requirement for the climatic factors-rainfall, wind speed, sunshine, humidity etc. [10,21,22,37,38]. The existing installed capacity scales of RE per unit area are normally constrained by the patterns as well as the changes of climate variables, and thus are sensitive to climate change. For solar energy, Beccali et al. found that the advantages of RE technologies strongly depend on the climate of the installation site [39]. The effects of renewable energy policy have been discussed in Beccali et al. , such as energy saving and greenhouse gas emissions [40].

2.3. Adaptive capacity of renewable energy system

Generally, adaptive capacity is defined as a country's or region's potential to respond to changes in the contribution of climate change to the RE system and ability to take advantage of or mitigate these changes. We disaggregate adaptive capacity into four categories: assets, flexibility, learning, and social organization [41,42]. Some indices in those categories are selected from their general application for capacity evaluation, such as the GDP per capita in assets.

2.3.1. Assets

Assets are defined as the resources a region has at its disposal to assist the RE industry in addressing climate change and its impacts. Assets are components of adaptive capacity because they represent the ability of a region to leverage resources in response to those climate risks in the RE system [41]. It is measured by physical, financial (average GDP per capita) and natural (installed capacity of RE) factors. A well-adapted area would have adequate levels of all three types of assets in order to leverage resources to adjust to change.

Specifically, the investment in energy infrastructure which is represented by the regional investment in water conservancy, environmental protection and communal facilities in the China Statistical Yearbook is used as a measure of a region's physical assets. The average GDP per capita from 2005 to 2010 recorded in the China statistical yearbook is used as the indicator of a country's financial assets. Scale effect in the form of per capita RE installed capacity, reflects the scale of RE installed capacities corresponding to different adaptive capacities to climate change.

2.3.2. Learning

Learning is defined as a country's organizational and institutional capacity to access and act on information. Learning is a component of adaptive capacity because it allows a country or a region to recognize and respond appropriately to environmental changes affecting its energy systems. An area that is adapting well would be able to acquire, synthesize, and incorporate new knowledge into decision making, including knowledge from resource users [43]. Therefore, two of the most critical components of learning are literacy rate [30] and student-teacher ratio of junior high schools.

2.3.3. Flexibility

Flexibility refers to the range of options a region has to meet its energy demand if the existing resource availability declines. Flexibility is a component of adaptive capacity because it represents the ability of a region to adjust through substitution of goods, such as alternative energy sources, production technologies, and accessibility to resources. A region with higher flexibility in production, trade and livelihood is expected to adapt better than those with lower flexibility.

In particular, we choose reserves of coal, oil and gas as an acceptable indicator to represent the ability to substitute RE if its supply plunges substantially. Furthermore, as a measure of income inequality, GINI index (a measure of statistical dispersion intended to represent the income distribution of a nation's residents) is also selected as an additional, indirect measure of a region's flexibility [44]. It is assumed that a region with a higher GINI coefficient will find it more difficult to allocate enough energy to cope with energy shortage.

2.3.4. Social organization

Social organization is selected as the degree to which a country's institutional and policy frameworks support or hinder RE development. Social organization is a component of adaptive capacity owing to its presentation of the ability of an area to effectively take steps towards mitigating climate change and implement policies and programs for successful adaptation. Government effectiveness index [45] and meteorological monitoring ability, which are common and flexible, are selected to represent the regional social organization ability. Specifically, the number of staffs and observatory stations for monitoring the climate variation are selected to measure the meteorological monitoring ability. The government effectiveness index produced by the Academy of Government in Beijing Normal University is used in this study.

3. Methodologies

3.1. General framework for renewable energy vulnerability to climate change

Based on the definition of vulnerability and its three dimensions mentioned above, as well as a literature review on vulnerability scoping diagram (VSD) from Polsky et al [30], we design the VSD for renewable energy vulnerability assessment, as is shown in Fig. 1. It can be seen from Fig. 1 that we divide RE vulnerability into
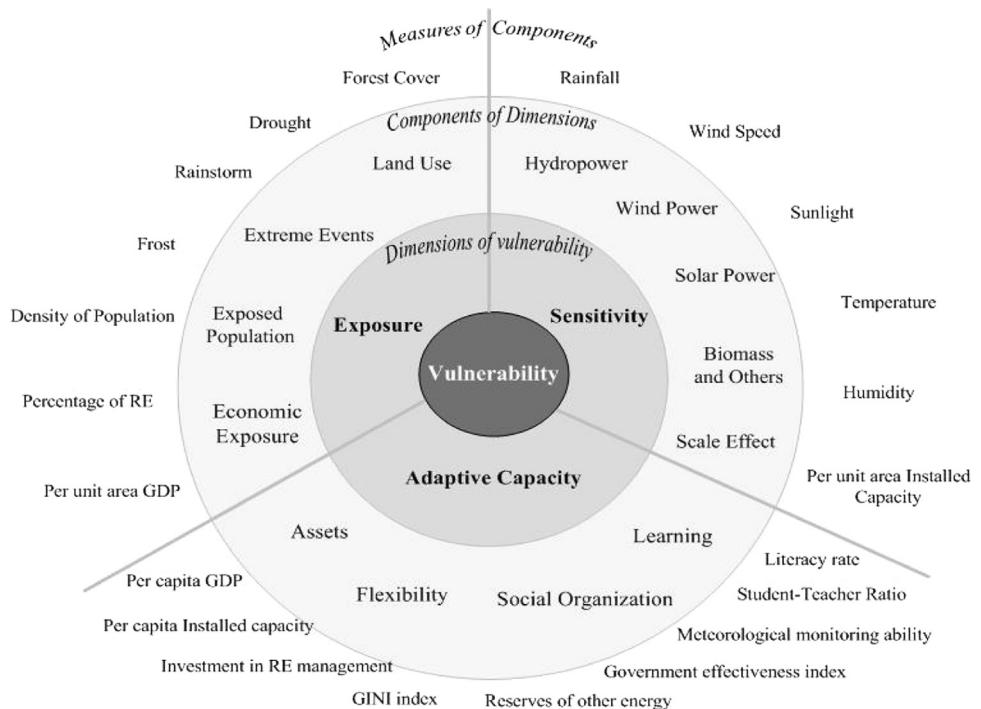

Fig. 1. VSD of renewable energy to climate change. *Note*: Hazard=climate change, and Exposure Unit=renewable energy system.

three dimensions, and then choose the representative components according to the literature (described in Section 2) for each dimension. Finally, some measures for each component are interpreted according to the literature review and data availability.

The research roadmap for renewable energy vulnerability assessment is represented as follows. Based on the literature review and data availability, we present the VSD for renewable energy vulnerability assessment (see Fig. 1, including the indictors for renewable energy vulnerability). This innovative framework is applied to China's regional vulnerability assessment by using the Grey Cluster Analysis method and the data from Tables 1 and 2. Finally, the decision theory, namely Simple Additive Weighting Approach, is applied to calculate the vulnerability score of regional RE systems. Based on the results by this method, some policy implications are obtained for the possible flash in the stability of energy systems and the strategies of adaptive capacity building.

For each indicator, we present its description and data sources respectively in Table 1 and Table 2. Apart from those indices mainly selected from the literature (labeled in Section 2), other indicators, due to their universal acceptability, are also chosen according to data availability and personal consideration.

It can be seen from Table 1 that the exposure to energy structure is embodied in the economic exposure and exposed population. Consistent with the sensitivity part in Fig. 1, the five climate elements in Table 1 are matched with the related RE generation.

The adaptive capacity and its four sub-indexes are demonstrated in Table 2. From these two tables and the framework, we can see that some indicators are distributed into multiple dimensions. Take GDP for example. A larger GDP scale represents the higher ability of one province to cope with climate change while it also implies a larger GDP loss resulting from the absence of RE supply due to a potential climate risk. Same is the case with the installed capacity of RE. It is crucial to deal with these double-feature variables to avoid the effects of those indicators on the decision results. In this regard, we adopt the convertible variables.

For example, per unit area GDP and per capita GDP represent the GDP in the exposure and ability dimension respectively. As for the items of installed capacity, we apply the per capita installed capacity and per unit area installed capacity (shown in Fig. 1) to deal with this double-feature variable in the fields of adaptive capacity and sensitivity, respectively.

3.2. Grey cluster method for the RE vulnerability to climate change

Renewable energy vulnerability assessment involves multiple impacts through numerous factors. The traditional regression analysis, ANOVA and principle component analysis (PCA) with high requirements on data resources cannot be used for this assessment. The grey relational analysis (GRA), however, can offset the shortage of rigorous data availability and sample distribution, which has been widely used for comprehensive analysis and risk assessment. Lu et al. [56] applied GRA to seize the dynamic characteristics and relative importance of impact factors between the different development stages of transportation system, and concluded that there is a positive relation between stable economic growth and energy intensity of vehicles. Jiang et al. [57] built a general framework for agricultural vulnerability assessment and used the expanded GRA method to measure the vulnerability in China. Their study found that the agriculture vulnerability is highest in western part of China, followed by central part with the lowest being in the southeastern coastal areas. A study by Lin et al. employed the GRA to research the relationships of economic growth, energy utilization and carbon emissions, and concluded that different sectors have different roles in carbon reduction [58].

As an important branch of Grey Cluster Analysis (GCA), grey relational analysis (GRA) is based on the grey incidence matrix, which is established according to the grey relevance degree of data series. Its mathematical mechanism was from the work of Deng [59] and Liu et al. [60], which is basically used to research the relative importance of those research objects. Our study employs

Table 1
Summary of indicators for exposure and sensitivity.

Dimension	Component	Indicator	Data source
Exposure	Economic exposure	Per unit area GDP, Proportion of RE	National Bureau of Statistics of China [46]; Department of Energy Statistics of National Bureau of Statistics [47]
	Exposed population	Density of population, proportion of RE	NBSC [46]; Department of Energy Statistics of National Bureau of Statistics [47]
	Extreme events	Frequency of drought, rainstorm and frost	China Meteorological Administration (CMA) [48]
	Land use	Forest cover	NBSC [46]
Sensitivity	Climate elements	Rainfall Temperature Wind speed Sunlight and humidity	NBSC [46] and CMA [49]
	Scale effect	Installed capacity scales of RE	Chinese Wind Energy Association [50]; China Power Yearbook [51]

Table 2
Summary of adaptive capacity indicators.

Category	Indicator	Measures	Date source
Assets	Per capita GDP	Financial assets	Calculation based on NBSC [46]
Assets	Investment in energy infrastructure	Physical infrastructure	NBSC [46]
Assets	Installed capacity of RE	Natural assets	Chinese Wind Energy Association[50]; China Power Yearbook [51]
Learning	Literacy rate	General educational level	Ministry of Education (MOE) [52]
Learning	Student-teacher ratio of junior high school	General educational level	MOE [52]
Flexibility	GINI index	Income inequality	Chen [53]; Tian [54]
Flexibility	Reserves of coal, oil and gas	Ability to supply enough energy	NBSC [46]; DES-NBSC [47]
Social organization	Government effectiveness index	Overall quality of governance	Research results from Beijing Normal University [55]
Social organization	Meteorological monitoring ability	Overall quality of RE management	China's Meteorological Disasters Yearbook [48]

this model to classify and identify the features of regional RE vulnerability during each category.

The core of GCA method is the build of absolute degree of grey incidence and grey incidence matrix. The absolute degree of grey incidence can be defined as follows:

(1) There are some data series for each province. X_i $(X_i = (x_i(1), x_i(2), ..., x_i(n)),)$ is the initial data series of province i, and $X_i \cdot D$ $(X_i \cdot D = (x_i(1) \cdot d, x_i(2) \cdot d, ..., x_i(n) \cdot d)$ and $x_i(k) \cdot d = x_i(k) - x_i(1), (k = 1, 2, ..., n))$ are the initial annihilation image of X_i, between which D is the initial annihilation operator. Thus, we could get the concept $s_i = \int_1^n (X_i - x_i(1)) dt$ for step 2.

(2) Suppose that the data series of two provinces are $X_i = (x_i(1), x_i(2), ..., x_i(n))$, and $X_j = (x_j(1), x_j(2), ..., x_j(n))$, which have the initial annihilation image of $X_i \cdot D$ and $X_j \cdot D$, namely $X_i^0 = (x_i^0(1), x_i^0(2), ..., x_i^0(n))$ and $X_j^0 = (x_j^0(1), x_j^0(2), ..., x_j^0(n))$, respectively. If $s_i - s_j = \int_1^n (X_i^0 - X_j^0) dt$, $\varepsilon_{ij} = 1 + |s_i| + |s_j|/1 + |s_i| + |s_j| + |s_i - s_j|$, the ratio ε_{ij} can be called as the absolute degree of grey incidence between X_i and X_j.

Based on the definition of the absolute degree of grey incidence, we can establish the grey incidence matrix for RE vulnerability assessment among the provinces. Assuming that the selected 31 provinces have a data series to demonstrate the exposure aspect of RE vulnerability and we choose m measures to represent the exposure unit, for example, we can obtain the following sequences:

$$X_1 = (x_1(1), x_1(2), ..., x_1(31))$$

$$X_2 = (x_2(1), x_2(2), ..., x_2(31))$$

$$......$$

$$X_m = (x_m(1), x_m(2), ..., x_m(31))$$

$\forall\, i \leq j; i, j = 1, 2, ..., m$, we can calculate the absolute degree of grey incidence ε_{ij} between X_i and X_j. Thus, the grey incidence matrix can be obtained as follows:

$$A = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{12} & \cdots & \varepsilon_{1m} \\ & \varepsilon_{22} & \cdots & \varepsilon_{2m} \\ & & \ddots & \vdots \\ & & & \varepsilon_{mm} \end{bmatrix} \qquad (1)$$

where $\varepsilon_{ij} = 1 + |s_i| + |s_j|/1 + |s_i| + |s_j| + |s_i - s_j|$.

We can get the matrix A by Eq. (1) and select the critical value $r \in [0, 1]$ (generally $r > 0.5$). If $\varepsilon_{ij} \geq r(i \neq j)$, X_i and X_j can be divided into the same group. In this paper, we designate a value of 0.9 for r in this study and obtain the cluster results for the three dimensions (exposure, sensitivity and adaptive capacity) of RE vulnerability based on the data in Tables 1 and 2.

3.3. Data sources and calculation process

Within the framework of Section 3.1, we can see that the vulnerability can be divided into three dimensions: exposure, sensitivity and adaptive capacity. It is assumed that there are high substitution rates among those dimensions. The index values were standardized based on maximum values in our dataset and placed on a scale of zero to one using Eq. (2). Each dimension is calculated by the weighted average of those index values under this dimension. As for every dimension, we suppose that its range is between 10 and 100. Then, we use Eq. (3) to obtain the value for each dimension. Given that vulnerability is divided into three components: the exposure, sensitivity, adaptive capacity and it is caused by the exposure, sensitivity and the shortage of adaptive capacity,

it is calculated by Eq. (4).

$$x = (X - X_{min})/(X_{max} - X_{min}) \qquad (2)$$

$$y = 10 + (Y - Y_{min})/(Y_{max} - Y_{min}) \times 90 \qquad (3)$$

$$V = (Exposure + Sensitivity) - AdaptiveCapacity \qquad (4)$$

The vulnerability scores are in turn standardized so that 0 is the lowest possible vulnerability score and 270 is the highest possible vulnerability score. Due to this standard process, these calculated scores are relative and only meaningful as they relate to the data set. We calculated the percentage of vulnerability explained by each variable (exposure, sensitivity, adaptive capacity) using Principal Component Analysis (PCA) [61]. Thus, with the vulnerability scores in different regions, we will determine the underlying reason for the vulnerability of regional RE systems.

The data sources for the base year 2010 in this study are from the following data sources, such as the China Statistical Yearbook, China Energy Statistical Yearbook, China Power Yearbook, China Meteorological Yearbook, China Meteorological Disaster Yearbook, China New Energy and Renewable Energy Yearbook, China Statistical Yearbook on Environment, Educational Statistics Yearbook of China, etc. [46–52]. More details can be found in Tables 1 and 2.

4. Results and discussions

4.1. Current development of renewable energy in China

In the context of robust energy demand, deteriorative environmental pollution and huge pressures of reducing emissions [62], China has been facing a series of dilemmas in the course of constituting climate change policies and energy security strategies. These facts have promoted the development of renewable energy, which is also intended for the social benefit in terms of health and quality of life (WHO [63]). Based on the market-oriented promotion and national policy, the renewable energy industry has witnessed a marked growth. Based on the data of [50,51] and [64], Fig. 2 demonstrates the renewable energy potential of China.

Fig. 2(a) and (b) shows the installed capacity of hydropower generation and wind power generation. The solar power [64] and biomass potential are shown in Fig. 2(c) and (d), respectively. It can be seen from these drawings that the hydropower utilization is concentrated mainly in southwest, central and southeast part of China, coinciding with the distribution of river basins. Wind power generation mainly comes from the three Norths (northeast, northern and northwest) and coastal parts of China, while the interior provinces are the areas of scarcity. Compared with Sichuan basin, Plateau area, including Tibet, Xinjiang and Qinghai is more suitable for solar energy utilization. Furthermore, major grain-producing areas are associated with the pattern of biomass production as shown in Fig. 2(d).

4.2. Spatial patterns of renewable energy vulnerability

Based on the data collected from Tables 1 and 2 , we apply the Grey Cluster Analysis to calculate the cluster results for the three dimensions of RE vulnerability. The cluster results for the exposure, sensitivity and adaptive capacity are demonstrated in Fig. 3(a)–(c) respectively.

The Exposure-G1 in Fig. 3(a) has the feature of high frequency of extreme events while the Exposure-G2 is the areas surrounding Beijing and Tianjin cities with a similar situation for land use. Exposure-G3 includes two provinces in northeast and three regions from northwest, which have the lower economic and population exposure. The shared characters, however, are difficult to detect from other groups. The reason may lie in that the cluster
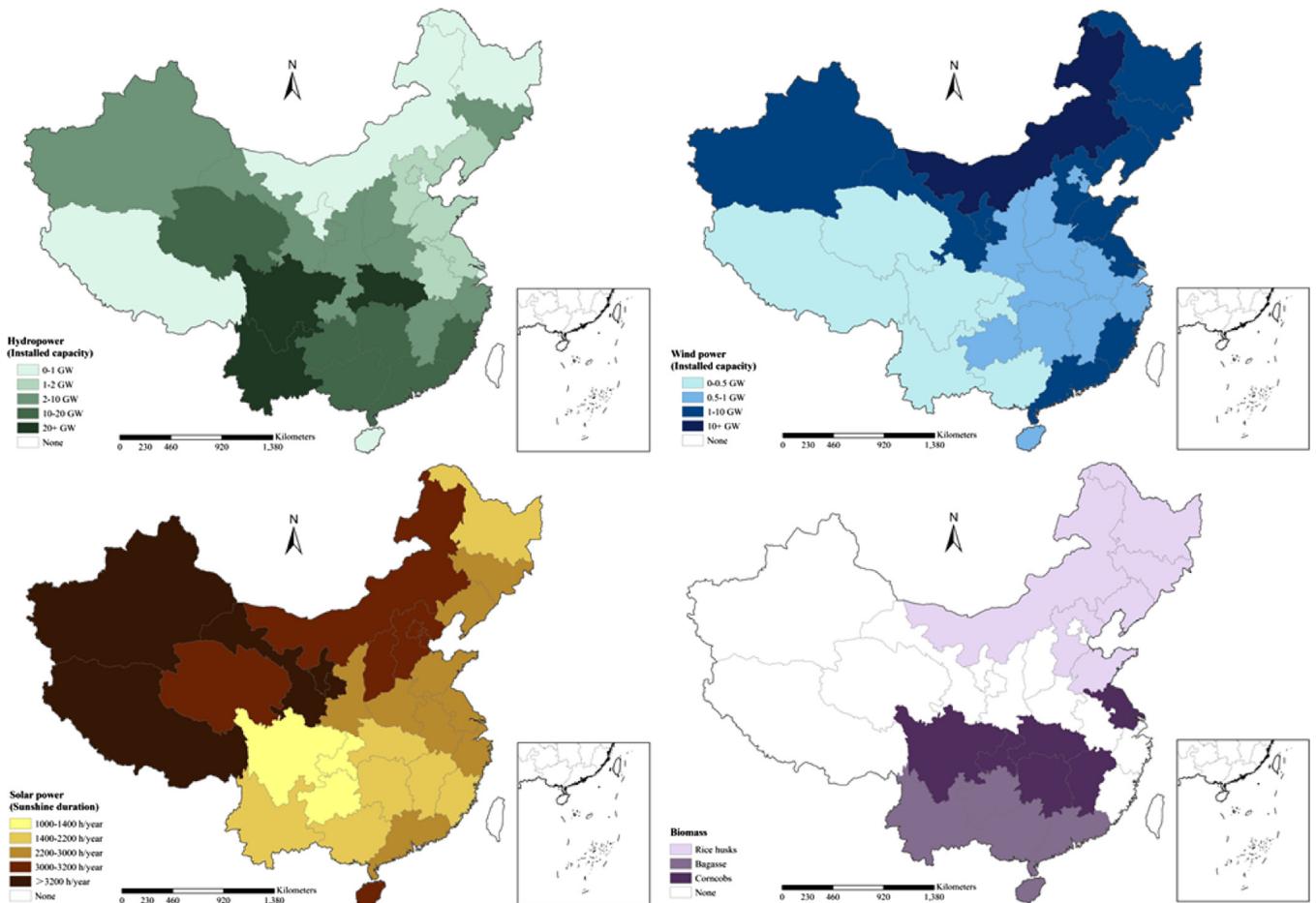
Fig. 2. Renewable energy potential of China. *Note*: It is a schematic map and does not imply definitive boundaries. The unit of measurement for solar power is sunshine hour per year.

results are determined by the combination of natural characteristics (land use, extreme events), social indicators and the moderator variable of the share of RE, which is embodied in the index of economic exposure and exposed population.

As for the sensitivity part in Fig. 3(b), we mainly consider climate elements and scale effects, which coincide with the utilization of renewable energy. Thus, this fact results in the sensitivity map with the feature of regional convergence, which means that because of similar traits, those adjacent regions can be clustered into the same class. In terms of adaptive capacity, AC-G1 in Fig. 3(c) includes Beijing, Tianjin and Shanghai and AC-G2 is located in east coastal area. These two groups belong to the areas with good adaptability whilst the AC-G5 has the lowest ability and AC-G6 contains the 7 central and southern provinces with the middle level of adaptive ability. The third and fourth categories are more scattered. The reason may be that some indicators of the M provinces with high similarity can result in clustering into one group while some other provinces which have a close relation with certain provinces among M provinces in the rest of the indicators can be merged into a group. This can lead to dispersive results, which increase the difficulty to interpret the underlying mechanism.

4.3. Regional assessments of renewable energy vulnerability

Region-specific vulnerability scores range from 0 to 199.20 (Table 3). Single variable regression results indicate that sensitivity has a greater influence on vulnerability compared to exposure and adaptive ability. The PCA revealed that the exposure, sensitivity and adaptive ability explain 40.61%, 32.25% and 27.14% of the variation in vulnerability scores, respectively. The exposure values are driven largely by Guangdong, Jiangsu and Shandong, which have very high exposure scores (100.00, 84.14 and 75.45 respectively).

The component scores for each province indicate that there is no single driver of vulnerability or a single underlying mechanism that makes a regional renewable energy system particularly vulnerable to climate change; rather, areas experience vulnerability as the result of a unique combination of adaptive capacity, sensitivity and exposure (Fig. 4). As shown in Fig. 4, the location of every province is determined by the proportion of the three dimensions in the vulnerability score of each region. Those total vulnerability scores have been divided into three classes- high, middle and low- which is shown by the color for each region.

In this way, we can identify provinces whose particular combination of factors warrant greater attention or provide an interesting combination of factors for further evaluation. For example, Guangdong and Gansu are the most vulnerable regions overall, but the drivers of their high levels of vulnerability differ vastly: Guangdong has the highest exposure levels while Gansu's vulnerability results from high sensitivity to climate change and the low level of adaptive capacity. Gansu's sensitivity score is driven by its close proximity to the 11053.95 MW vulnerable installed capacity, and Gansu's average climate conditions are quite different from the mid-level of those elements, resulting in a relatively larger accumulative total. Unlike Gansu, other regions with a similarly high sensitivity scores, such as Tibet, Qinghai, Inner Mongolia, Sichuan and Hubei, have relatively lower

a
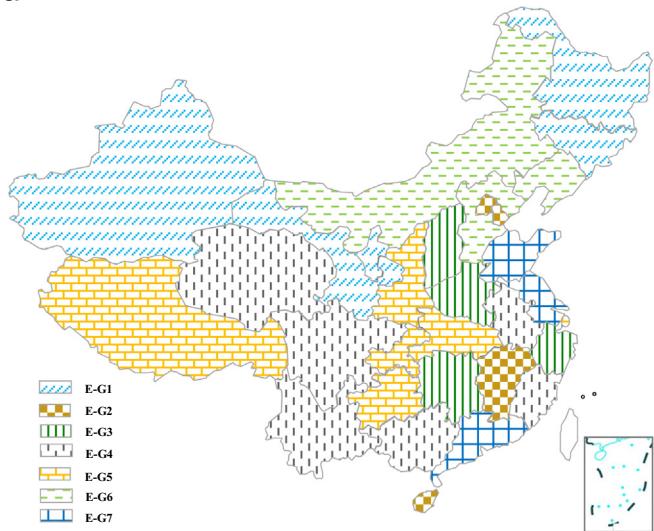
b
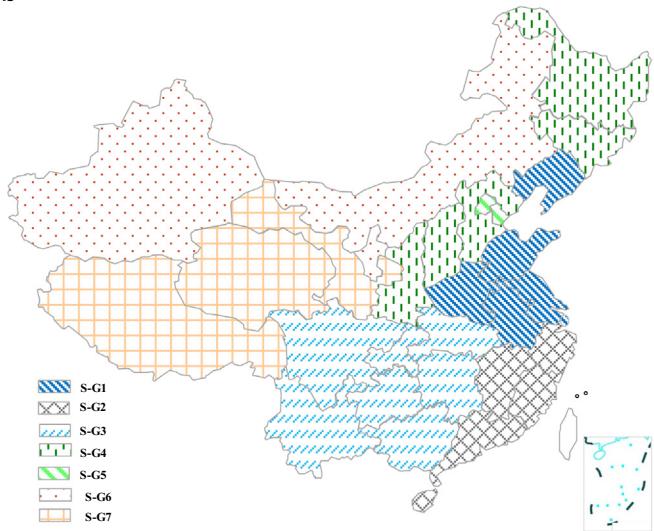
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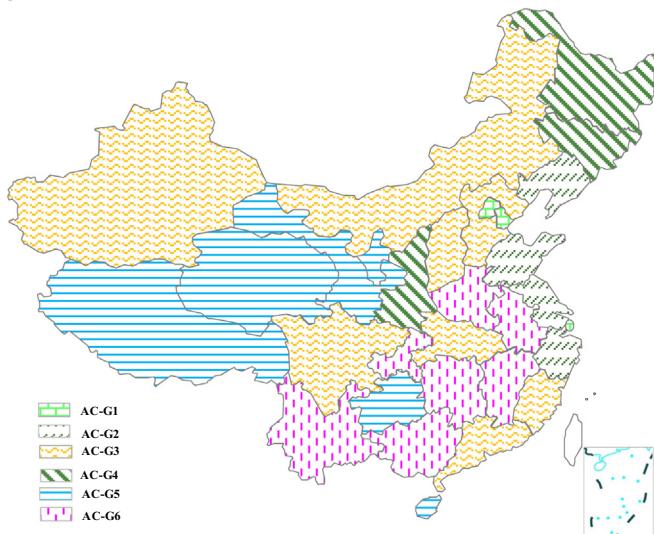
Fig. 3. Cluster results on three dimensions of renewable energy vulnerability. *Note*: The E-G1 is the abbreviation of Exposure-Group1 as well as for the others. It is a schematic map and does not imply definitive boundaries. (a) Exposure, (b) sensitivity and (c) adaptive capacity.

Table 3
Standardized exposure, sensitivity, adaptive ability and vulnerability scores.

Region	Exposure	Sensitivity	Adaptive capacity	Vulnerability
Guangdong	100.00	84.96	56.16	199.20
Gansu	57.62	86.93	31.38	183.57
Tibet	13.44	96.13	10.00	169.97
Qinghai	34.72	90.67	29.13	166.67
Inner Mongolia	61.10	96.11	61.08	166.52
Ningxia	56.05	58.70	32.28	152.87
Xinjiang	52.43	77.67	54.47	146.03
Hainan	32.38	71.40	33.83	140.35
Sichuan	23.82	100.00	60.72	133.49
Heilongjiang	58.51	55.06	51.90	132.07
Hebei	63.86	50.07	56.84	127.49
Guangxi	28.70	67.17	44.50	121.77
Guizhou	13.22	69.59	33.20	120.01
Jilin	46.33	51.76	49.73	118.76
Shanxi	41.63	56.28	54.21	114.10
Hunan	40.03	49.38	46.06	113.75
Hubei	17.43	86.01	61.77	112.07
Liaoning	60.05	44.42	64.01	110.85
Yunnan	30.59	48.04	40.14	108.90
Jiangxi	31.03	45.43	42.16	104.70
Shandong	75.45	19.99	61.94	103.90
Jiangsu	84.14	18.07	68.91	103.69
Henan	45.04	31.38	44.89	101.94
Fujian	26.67	58.36	54.25	101.18
Zhejiang	42.88	45.45	66.53	92.20
Chongqing	10.00	44.85	40.54	84.72
Anhui	28.08	18.66	37.69	79.44
Shaanxi	23.50	21.00	50.67	64.23
Beijing	31.60	46.46	84.38	64.08
Tianjin	36.84	33.18	86.32	54.10
Shanghai	19.60	10.00	100.00	0.00
Mean	41.51	55.91	51.93	115.89

Note: Vulnerability=(exposure+ sensitivity)-adaptive ability.

vulnerability scores due to their different levels of exposure and adaptive capacity. Tibet, a region with the lowest adaptive capacity scores and relatively higher sensitivity features, however, ranks third because of its lower exposure unit. Tibet's exposure score is determined by its low economic development level as well as its relatively lower percentage of renewable energy.

A number of western areas, including Ningxia, Xinjiang, and Qinghai, have higher vulnerability scores than average level, despite their relatively small percentage of renewable energy installed capacity. These regions have very low adaptive capacity scores and higher-than-average levels of sensitivity to climate change. Other categories of vulnerability including Hainan, Sichuan, Guangxi and Guizhou are found in these southern areas with lower-than-average levels of adaptive capacity and lower exposure unit, resulting in the slightly higher-than-average vulnerability scores.

Due to the relatively stable situation for exposure and sensitivity unit, the adaptive capacity stands out as an essential part for vulnerability management. As described in the PCA and regression analyses, adaptive capacity plays an important role in determining vulnerability scores. Further analysis on the indicators used in the adaptive capacity scores reveals patterns among the regions (see Table 4). While Table 3 shows the standardized scores for vulnerability and its three dimensions (exposure, sensitivity and adaptive capacity), Table 4 presents the standardized scores for adaptive capacity and its four sub-indexes (see Section 2.3). First, there is not much variation in the social organization scores, ranging from 0.00 to 0.76 with most of them below 0.30. Flexibility scores are consistently low for the 31 provinces (with scores ranging from 0.06 to 0.64), and often less than 0.50 due to the consistently poor GINI scores. The differences in adaptive capacity, therefore, are
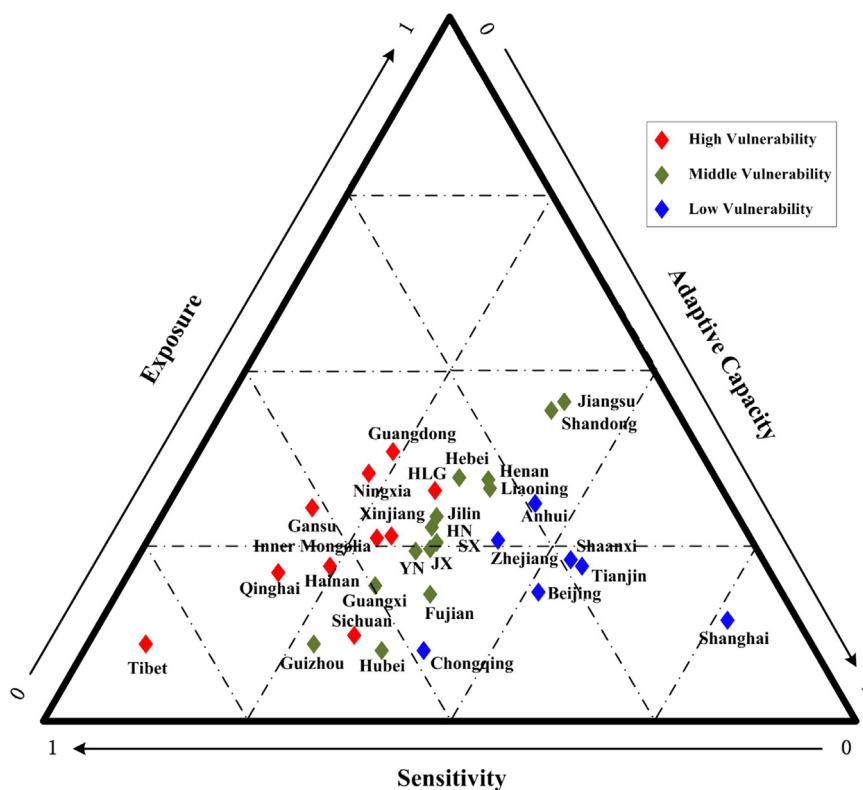
Fig. 4. Ternary plot for the pattern in the combination of vulnerability scores. *Note*: HLG, HN, SX, JX and YN are the abbreviation of Heilongjiang, Hunan, Shanxi, Jiangxi and Yunnan respectively.

Table 4
Scores for the components of adaptive capacity.

Region	Assets	Flexibility	Learning	Social organization	Adaptive capacity total
Tibet	0.02	0.15	0.23	0.00	0.40
Guizhou	0.19	0.12	0.36	0.07	0.74
Qinghai	0.17	0.06	0.55	0.06	0.85
Gansu	0.14	0.18	0.54	0.07	0.93
Ningxia	0.10	0.16	0.58	0.09	0.93
Yunnan	0.29	0.17	0.46	0.07	0.99
Hainan	0.08	0.15	0.62	0.15	1.00
Anhui	0.09	0.22	0.56	0.25	1.12
Chongqing	0.17	0.24	0.64	0.12	1.16
Guangxi	0.22	0.19	0.60	0.17	1.17
Jiangxi	0.11	0.26	0.62	0.20	1.19
Henan	0.13	0.26	0.59	0.26	1.24
Guangdong	0.36	0.12	0.56	0.33	1.37
Hunan	0.22	0.20	0.83	0.19	1.45
Sichuan	0.39	0.44	0.58	0.17	1.58
Shaanxi	0.12	0.50	0.77	0.20	1.60
Jilin	0.19	0.33	0.92	0.19	1.63
Shanxi	0.12	0.55	0.77	0.22	1.66
Fujian	0.30	0.33	0.82	0.22	1.67
Heilongjiang	0.12	0.50	0.86	0.21	1.68
Hubei	0.44	0.32	0.75	0.23	1.74
Hebei	0.18	0.47	0.83	0.28	1.77
Xinjiang	0.11	0.64	0.91	0.14	1.79
Inner Mongolia	0.35	0.50	0.79	0.16	1.80
Shandong	0.23	0.39	0.76	0.48	1.86
Zhejiang	0.36	0.32	0.76	0.48	1.93
Liaoning	0.26	0.46	0.89	0.36	1.97
Jiangsu	0.31	0.32	0.86	0.61	2.10
Tianjin	0.59	0.50	0.98	0.45	2.52
Beijing	0.42	0.50	1.00	0.65	2.56
Shanghai	0.67	0.47	0.85	0.76	2.74
Mean	0.24	0.32	0.71	0.25	1.52

driven largely by differences in assets and learning. For example, the region with the lowest adaptive capacity score, Tibet, has a score of 0.02 for assets and 0.23 for the learning while the province with the highest adaptive capacity point, Shanghai, has scores of 0.67 and 0.85, respectively.

There are different and region-specific adaptive strategies for those top vulnerable areas. First, the local government of Guangdong should enhance the ability to cope with the extreme events and emergency management in order to reduce the exposure level, which will also benefit the improvement of its adaptive capacity. Second, as for the western provinces, such as Tibet, Gansu, Ningxia, Xinjiang and Qinghai, there are many possibilities to develop the adaptive capacity. The adaptive strategies, however, are quite different for each of those western regions. Tibet should enhance all aspects of capacity while Gansu, Ningxia and Qinghai require the improvement of assets, flexibility and social organization and Xinjiang only need to focus on the assets unit. Third, as one of the most important wind power bases in China, Inner Mongolia should facilitate the meteorological monitoring ability to enhance the sensitivity situation, which is also beneficial to the advance of social organization capacity. Finally, due to the relatively lower percentage and potential of RE and the frost extreme, Heilongjiang province could remain in the current status.

5. Conclusions and policy implications

Renewable energy featuring wide distribution, huge potential and sustainable utilization is a significant and indispensable part of energy systems. Given the fact that the extremely high proportion of fossil fuel is the root cause of environmental problems, the electricity generation from hydropower, wind power and solar energy should be prioritized by the Chinese government in a bid to mitigate air pollution and ensure energy security.

The development of renewable energy, however, is vulnerable to climate change. The extreme events (including rainstorms, frost etc.) and the variation of climatic elements may have substantial impacts on renewable energy. This paper combines the GCA model with the Simple Additive Weighting Approach to measure the renewable energy vulnerability caused by the excessive exposure and sensitivity and/or the lack of adaptive capacity.

5.1. Conclusions

The aim of this study is to develop a regional or nation-specific policy relevant vulnerability assessment framework concerning renewable energy system in terms of climate change. We draw on a range of data sources and use theoretical basis to build a vulnerability index in view of exposure, sensitivity and adaptive capacity.

Based on the results, we condense the following conclusions:

(1) The general framework for RE vulnerability assessment adopted by our study can be applied to other areas. Furthermore, vulnerability assessment is meaningful to engage policy-maker and RE investors collectively to provide qualitative contextual risk rankings as a first step to determine their strategies. Subsequently, the VSD framework will be valuable for policy decision as well as the subsequent energy system vulnerability assessment.

(2) The renewable energy endowment reflects the status of RE development and the sensitivity unit of vulnerability. Renewable energy is particularly vulnerable to the climatic elements, which coincides with the distribution of RE potential. This feedback mechanism is the root cause of RE vulnerability. Thus, the vulnerability management should consider the renewable energy endowment, namely the percentage of RE in energy structure and installed capacity of RE, which is implied in the three parts of vulnerability.

(3) According to the vulnerability clustering results, the sensitivity cluster result corresponds to the potential distribution of RE while the exposure and adaptive capacity unit represent the complexity and disperse distribution. The reason may be that unlike the indicators of sensitivity, the exposure and adaptability indices contain the social and natural vulnerable factors, which are combined to produce the integrated product. In this sense, social and natural risk factors both should be considered in vulnerability management.

(4) Based upon the vulnerability assessment results, it is demonstrated that compared with the least vulnerable city Shanghai, Guangdong province has the highest vulnerability scores and the western part of China has higher vulnerability than the average level. In terms of RE development, the most important result found in this study is the increasing RE vulnerability of the poorer regions of China to climate change.

(5) From the principle component analysis, it was obvious that there was no single driver of vulnerability or a single underlying mechanism that renders a regional renewable energy system particularly vulnerable to climate change. Rather, areas experienced vulnerability due to a unique combination of adaptive capacity, sensitivity and exposure. Furthermore, the adaptive capacity is an important segment of vulnerability management. In addition, the regional differences of adaptability can trace its root in the diversity of assets and learning ability.

5.2. Policy implications

The development of renewable energy sources is essential for the sustainable economic and social development in China.

Climate change, however, has become a key factor restricting China's renewable energy development having the potential to fluctuate energy supply. Based on the renewable energy vulnerability assessment model, the results reveal the following important implications:

(1) As a sustainable and portable energy source, the RE development should consider the features of vulnerability. Further, every region should adopt different and specific strategies for RE utilization. With relatively higher vulnerability in Guangdong province and western provinces, efforts should be made to improve adaptive ability instead of the large-scale and blind use of renewable sources. It may be a wiser choice for these areas to develop the small distributed RE systems.

(2) Due to its central role in vulnerability management, the building strategy of adaptive capacity is divisional for different part of China. Regions should facilitate the improvement of social organization ability, with the exception of Shanghai, Beijing, Tianjin, Zhejiang, Jiangsu and Shandong. Unlike the major enhancement of assets in Hainan, Anhui, Xinjiang, Shaanxi, Heilongjiang and Shanxi, the top 6 high vulnerability provinces should perfect their overall ability sub-indicators.

(3) The proposal for the RE vulnerability assessment is an essential part of policy-making and investment in renewable energy systems as well as the response for addressing climate change. The urgency of energy security calls for heightened research on the energy system vulnerability assessment, especially the evaluation for the most relevant energy sector- renewable energy in the context of climate change. Because of differences in resource endowments, economic capacity, education level, there is a huge gap among different parts of China in terms of the RE vulnerability. For example, despite its being one of the bases for the wind power development in China, Inner Mongolia's frozen extreme weather and lack of wind power consumptive capacity have become the main obstacles to its RE development.

This paper is an application of VSD. Popularizing the VSD method is challenging and requires subjective judgments on the representative measures by the researchers. However, there is voluminous literature about the potential impact factors of renewable energy in view of climate change. Based on the literature analysis and data availability, we construct the framework for renewable energy vulnerability assessment and verify its feasibility. However, there is much room to improve in terms of the decision-making method for the comparable vulnerability score. AHP or TOPSIS perhaps could be a better choice in this regard. With a more systematic literature analysis [65], the application of this framework on a larger scale and the dynamic assessment of RE vulnerability, considering sensitivity analysis [66,67] for vulnerability assessment would hopefully come to realization, provided the framework is established.

Acknowledgments

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